Temporal Feature Selection for Optimizing Spatial Filters in a P300 Brain-Computer Interface

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H. Cecotti[1], B. Rivet[2]

Abstract— **For the creation of efficient and robust Brain-Computer Interfaces (BCIs) based on the detection of event-related potentials (ERPs) in the electroencephalogram (EEG), spatial filtering has been shown as being an important step for feature extraction and reduction. Current spatial filtering methods for ERP enhancement typically consider a global approach by enhancing the signal on a predefined time-segment that contains all the different ERP components, which can have different spatial distributions. Because several ERP components occur, it is likely that they have different neural sources, and require specific signal processing methods. We propose to use a spatial filtering method based on the maximization of the signal-to-signal plus noise ratio, and compare different approaches to determine the best time segment for optimizing the choice of the spatial filters. The evaluation was carried out on data recorded of ten healthy subjects during a P300 speller experiment. The results support the conclusion that spatial filters based on the global approach provide the best solution and outperform local and hybrid approaches.**

I. Introduction

Non-invasive Brain-Computer Interfaces (BCIs) using electroencephalogram (EEG) recordings represent a new means of communication, by decoding information from the brain. BCI research is typically aimed at improving the life of severely physically impaired people, such as locked-in patients, by providing adapted communication devices [1], and also tools for improving rehabilitation [2], [3]. To answer the specific needs of patients, BCI must be robust and reliable, *e.g.*, the accuracy of commands detection should be sufficiently high to not frustrate the user [4]. The detection of event-related potentials (ERPs) is one of the main common approaches for the creation of reliable BCIs. ERPs represent voltage fluctuations caused by the post synaptic neural activity of cortical pyramidal neurons, which are time-locked to events [5]. For non-invasive BCIs, ERPs are measured using electrodes placed on the surface of the scalp. The features of the ERP components, such as the amplitude and the latency, are typically assumed to be stable when a subject is performing a task, *e.g.*, when a subject pays attention to a particular stimulus [6], [7]. Virtual keyboards based on the detection of ERPs have been used in BCI, the most famous variation is the P300 keyboard [8], and new variations based on other ERP components have been proposed [9].

A key component for feature extraction in single-trial EEG classification is the knowledge of the type of brain responses that should be classified. Although efficient methods have been presented in the literature that do not include problem-related knowledge inside the signal processing and classification pipeline, the best methods often use some neuroscience knowledge or assumption for the creation of a detection system. First, it is important to know the frequency bands of the relevant brain activity to discriminate. Second, sensor location can be optimized to observe the signal where the relevant information is present. Particularly, spatial filtering has become a necessary step for extracting discriminant features for the classification of brain responses in the EEG. Spatial filtering methods often assume that the spatial distribution of the brain responses is stable over time, which allows to project the EEG signal to a lower dimensional space, reducing the spatial dimension, *i.e.*, the number of electrodes. Although it is not true due to the non-stationarity of the EEG signal, and the nature of the tasks [10], this assumption allows to reduce the number of features. This approach has been largely used for motor imagery detection, with filters based on common spatial patterns [11]. For the detection of ERPs, such as the P300 (a positive deflection in voltage at a latency of about 300 ms in the EEG), most of the techniques focus on a global approach. They consider directly the set of ERP components related to the presentation of a particular stimulus, with spatial filtering as a preprocessing step [12]–[14] or not [15]. While the names of those approaches let suggest that they are dedicated to the P300 component, one of the main ERPs that is present to the target class for the classification, they embed other ERPs for the classification.

In this study, we propose to compare different strategies for the estimation of spatial filters: a global approach (the classical approach) where spatial filters are based on the whole set of ERP components, local approaches where spatial filters are based on specific ERP components, and finally, hybrid approaches where spatial filters are only applied on a specific time segment. The goal of this study is to determine to what extent the addition of specific knowledge from the ERP literature may improve the performance of single-trial detection. In addition, spatial filters that are based on the Rayleigh quotient often consider a set of spatial filters that maximize the same objective function, such as the maximization of the signal-to-noise ratio. A set of spatial filters where each filter maximizes different functions would provide a better set of features. The remainder of this paper is organized as follows. The proposed methods to provide the input features based on several spatial filtering strategies are described in Section II. The results are presented in Section III. Finally, the impact of the results are discussed in Section IV.

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II. Methods

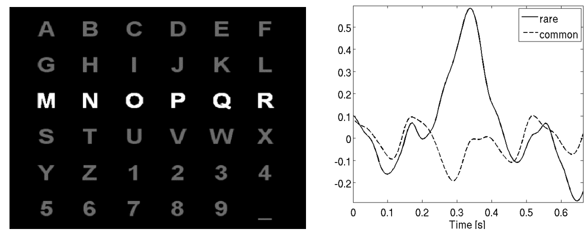
A. P300 speller

A P300 speller is a virtual keyboard that allows people to write characters (letters, digits, symbols) on a computer screen. It is based on the oddball paradigm, which is used to generate ERPs on targets selected by the user. A 6×6 matrix that includes all the available letters is presented to the user. To spell a letter, the user has to pay attention on the character s/he wants to spell. In the oddball paradigm, a letter is defined by a couple (row,column). The flashing lights are on each row and column, and not on each character. The character is supposed to correspond to the intersection of the accumulation of several ERPs. The best accumulation of ERPs for the horizontal (resp. vertical) flashing lights determines the row (resp. the column) of the desired character. When the user focuses on a cell of the matrix, it is possible to detect a P300 after the cell was intensified. In order to generate ERPs, the rows and columns are intensified randomly. Row/column intensifications were block randomized in blocks of 12 (6 rows and 6 columns). The sets of 12 intensifications are repeated N_{epoch} times for each character. $2N_{epoch}$ possible P300 responses should therefore be detected for the recognition of one character. The P300 speller is composed of two successive classification problems. The first classification task is to detect the presence of a P300 in the EEG signal. The second one corresponds to the combination of a minimum of two P300 responses for determining the correct character to spell. The detection of P300 responses corresponds to a binary classification: one class represents signals that correspond to an ERP on the target visual stimulus, the second class represents non-target visual stimuli. The order of the flashing lights allows knowing when a P300 response is expected.

B. Experimental protocol

Ten healthy subjects (age=25.5 ± 4.4 years old, three females) participated in a P300 speller experiment where each subject had to spell 40 characters in two sessions of 20 characters. The text to spell was identical across subjects. The P300 speller was displayed on a 27 inch LCD screen with a brightness of 375 cd/m2. Subjects were sitting on a comfortable chair at about 60 cm from the screen, in a non-shielded room. The stimulus onset asynchrony was set to 133 ms, and the inter-stimulus interval was 66 ms, the signal was recorded on O_1, O_2, P_3, P_4, P_7, P_8, P_Z and FC_Z. F_7 and F_8 were dedicated to the ground and the reference, respectively, as depicted in Fig. 2. The amplifier was a FirstAmp (Brain Products GmbH) with a sampling frequency of 2 kHz.

Figure 2 depicts the grand average waveform of ERP components that occur during the presentation of a visual stimulus in the P300 speller. The evoked response, and its main components (N200, P300), suggests that different neural sources are involved in the response. Hence, the different spatial distributions corresponding to each ERP component may be different, and it would require the use of several spatial filters to enhance the signal throughout the different time points of a trial.



(a) Graphical User Interface (b) P300 evoked potentials

Fig. 1. Representation of the P300-BCI Speller. Fig. II-B: the subject counts mentally each time the letter to spell is highlighted, Fig. 1(b): average P300 response on one sensor located on Cz.

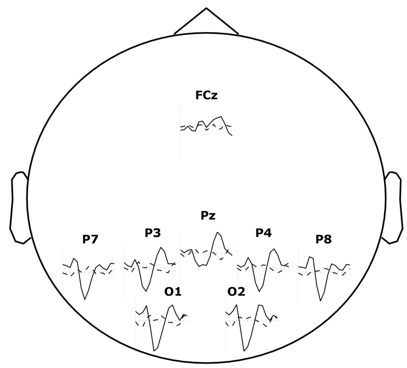


Fig. 2. Grand average waveform of the event-related potential components after the presentation a visual stimulus from the stimulus onset to 800 ms. (plain lines: target, dashed lines: non-target.

C. Feature extraction

The recorded EEG signal was first bandpass filtered (Butterworth filter, order=4) with cutoff frequencies at 1 and 12.5 Hz, then downsampled to 25 Hz. The next processing step was spatial filtering with the xDAWN technique, which maximizes the signal-to-signal plus noise ratio (SSNR) based on the Frobenius norm of a Rayleigh quotient [16], [17]. The relevant signal corresponds to the information relative to the presentation of a target. This process provides N_f spatial filters that are ranked in terms of their SSNR. The enhanced signal XU is composed of three terms: the ERP responses on a target class ($D_1 A_1$), a response common to all stimuli, *i.e.*, all targets (images with a person) and non-targets (images without a person) confound ($D_2 A_2$), and the residual noise (H), that are all filtered spatially with U.

$$XU \quad = \quad (D_1 A_1 + D_2 A_2 + H)U. \qquad (1)$$

where $\{D_1, D_2\} \in \mathbb{R}^{N_t \times N_1}$ are two Toeplitz matrices, N_1 is the number of sampling points representing the target and superimposed evoked potentials, and $H \in \mathbb{R}^{N_t \times N_s}$. The spatial filters U maximize the SSNR:

$$\text{SSNR}(U) = \text{argmax}_{\ U} \ \frac{\text{Tr}(U^T \hat{A}_1^T D_1^T D_1 \hat{A}_1 U)}{Tr(U^T X^T X U)} \qquad (2)$$

where $\hat{A}_1$ represents the least mean square estimation of A_1:

$$\hat{A} = \begin{bmatrix} \hat{A}_1 \\ \hat{A}_2 \end{bmatrix} = ([D_1; D_2]^T [D_1; D_2])^{-1} [D_1; D_2]^T X \quad (3)$$

where $[D_1; D_2] \in \mathbb{R}^{N_t \times (N_1+N_2)}$ is obtained by concatenation of D_1 and D_2, and Tr(.) denotes the trace operator.

During the experiments, four spatial filters ($N_f = 4$) were used. In the next section, we focus on the effect of N_1, the number of sampling points, and N_{t0}, the start of the segment of interest after the stimulus onsets, on single-trial performance. N_1 and N_{t0} can be set empirically, in relation to some prior knowledge, or optimized to maximize the SSNR. N_{t0} is usually set to 0, as the signal after the stimulus onset can contain relevant features, and N_1 is typically set to include the P300 ERP component.

D. Global and local spatial filtering

To isolate the spatial filtering step and consider inputs to the classifier with the same number of features, we propose the following methods for the estimation of a set of four spatial filters:

- (G) A global approach where a time-segment from the stimulus onset to 800 ms after the stimulus onset ($N_{t0} = 0$ and $N_1 = 20$). The set of spatial filters corresponds to the first four best filters.
- (L1) and (L2) are two local approaches. L1 considers a time segment from 100 ms to 300 ms after the stimulus onset, which is supposed to capture the N2 ERP component ($N_{t0} = 2$ and $N_1 = 5$). L2 considers a time segment from 300 ms to 600 ms after the stimulus onset, which is supposed to capture the P300 ERP component ($N_{t0} = 8$ and $N_1 = 8$).
- (H1) and (H2) are hybrid strategies that consider four segments: stimulus onset to 100 ms, 100 ms to 300 ms, 300 ms to 600 ms, 600 ms to 800 ms. With H1, the set of four spatial filters correspond to the best filter of each segment. The N_f filters are applied globally on the signal. For H2, the signal is spatially filtered on the different time-segments, and the four spatial filters correspond to the first four best filters applied on the different time-segments. In this case, the signal is spatially filtered locally (N_f filters on four different time segments).
- (GS) the grid search approach determines the start and the best length of the time segment by maximizing the SSNR as defined in the previous section. Spatial filters are created on a subset of the data for all the possible combination of (N_{t0}, N_1), then they are evaluated on a different subset, to determine the best parameters maximizing the SSNR.

$$(N_{t0}, N_1) = \text{argmax}_{(N_{t0}, N_1)}\ SSNR(U) \quad (4)$$

E. Binary classification

The input vector for the classifier was obtained by the concatenation of the N_f time-course signals across spatial filters. The detection score was obtained with the Bayesian linear discriminant analysis (BLDA) classifier [18]. The database contained two sessions for each subject with 4800 trials (800 for target, 4000 for non-target). Performance for single-trial detection was assessed by the area under the ROC curve (AUC) by considering a five-folds cross validation [19].

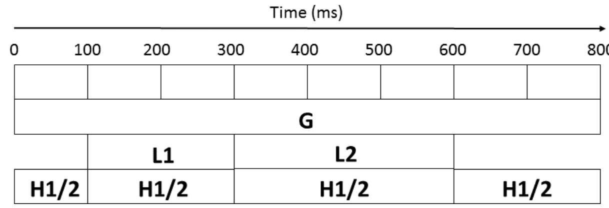


Fig. 3. Temporal windows (0 corresponds to the stimulus onset).

III. Results

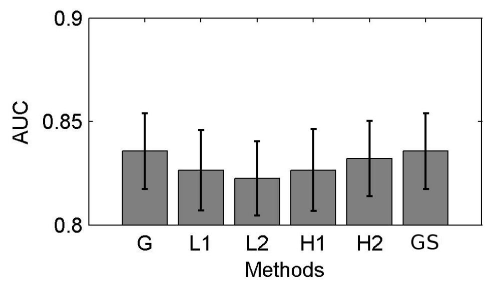


Fig. 4. Mean AUC across subjects for the six methods. The error bars represent the standard error.

The AUC for single-trial detection is presented in Table I. The main results are depicted in Figure III. For the method (G), the mean AUC across subjects was 0.836 ± 0.058. For (L1) and (L2), the AUC was 0.826 ± 0.061 and 0.822 ± 0.057, respectively. For (H1) and (H2), the AUC was 0.826 ± 0.062 and 0.832 ± 0.057. Finally, the AUC for (GS) was 0.836 ± 0.058. A Friedman's test revealed a difference across methods ($p < 10e-5$). After post-hoc analysis with a false discovery rate correction, (G) and (GS) provided better performance than the other methods. In addition, there is a significant difference between (L2) and (H2) (Wilcoxon sign rank test $p < 0.02$). Figure 5 depicts the spatial distribution with the method GS, the projection of the ERP waveform after spatial filtering (using the best spatial filter). The corresponding table representing the SSNR (arbitrary unit) as a function of the start of the time-segment (N_{t0}) and its length (N_t) are depicted in Figure 6.

These results show that the best spatial filters are obtained with almost the longest time segment, and all the ERP components should be taken into account. As an unexpected result, the spatial filters that are optimized for each individual ERP components ((H1) and (H2)), do not outperform the other methods. Indeed, it is better to select the first four best spatial filters that optimize the SSNR from the global segment instead of selecting each of the best spatial filter that optimizes a specific ERP component. The results suggest that the spatial distribution across the different ERP components is identical, and only a few components have a discriminant

TABLE I

AUC FOR EACH SUBJECT AND METHOD.

Subjects	G	L1	L2	H1	H2	GS
1	0.900 ± 0.037	0.888 ± 0.039	0.899 ± 0.037	0.902 ± 0.036	0.897 ± 0.034	0.901 ± 0.036
2	0.770 ± 0.040	0.740 ± 0.059	0.760 ± 0.037	0.754 ± 0.045	0.768 ± 0.050	0.770 ± 0.040
3	0.774 ± 0.039	0.767 ± 0.035	0.765 ± 0.040	0.769 ± 0.034	0.772 ± 0.047	0.775 ± 0.039
4	0.851 ± 0.068	0.835 ± 0.076	0.837 ± 0.058	0.841 ± 0.069	0.848 ± 0.071	0.851 ± 0.068
5	0.867 ± 0.066	0.864 ± 0.069	0.867 ± 0.066	0.857 ± 0.068	0.861 ± 0.068	0.867 ± 0.067
6	0.910 ± 0.045	0.910 ± 0.046	0.884 ± 0.055	0.908 ± 0.042	0.907 ± 0.046	0.910 ± 0.045
7	0.829 ± 0.029	0.823 ± 0.033	0.820 ± 0.032	0.800 ± 0.030	0.831 ± 0.035	0.829 ± 0.029
8	0.811 ± 0.052	0.808 ± 0.052	0.805 ± 0.051	0.810 ± 0.043	0.805 ± 0.055	0.811 ± 0.052
9	0.751 ± 0.049	0.745 ± 0.047	0.731 ± 0.040	0.735 ± 0.052	0.746 ± 0.051	0.751 ± 0.049
10	0.893 ± 0.027	0.884 ± 0.031	0.857 ± 0.030	0.888 ± 0.021	0.885 ± 0.027	0.893 ± 0.027
mean	0.836	0.826	0.822	0.826	0.832	0.836
sd	0.058	0.061	0.057	0.063	0.057	0.058

power. As the experiments were carried out with only eight sensors mainly located on the parietal and occipital area, a larger set of electrodes may show different results.

IV. Discussion and conclusion

To increase the reliability of single-trial detection, it is important to determine parameters such as the bandpass filtering frequencies [20], the sensors [21], and the time segment that should be used [22]. While prior knowledge of the problem may help to determine how to process the signal, we have shown that between an optimized selection of the time-segment, a global time-segment, and a local time-segment, the predefined time segment that contains a set of ERP components is the most efficient. It has been shown in the literature that spatial filtering is a key component for the detection of event-related potentials in the EEG signal for the creation of brain-computer interfaces. However, several ERP components are present in the EEG signal, and it was rather unknown whether spatial filtering should be applied in relation to this information, or if it has to be ignored. Including more information about brain processes into the signal processing pipeline should enhance performance. Yet, we have shown that specific ERP characteristics were not needed, and that the xDAWN method for extracting spatial filtering was the best when a long time segment is considered. In addition, we have shown that there was no difference between applying globally spatial filters that are optimized for different time segments, and applying locally those spatial filters. Finally, it seems that the ERPs evoked during P300 speller experiment do not require independent spatial filtering. Further works should be carried out for adapting spatial filtering for applications where the tasks, and therefore the ERP components, vary over time. Contrary to the P300 speller that requires a steady attention during the task, the addition of a new attentional task, or changes in the environment may change the ERP features, thus requiring an adaptation of the spatial filters.

Acknowledgment

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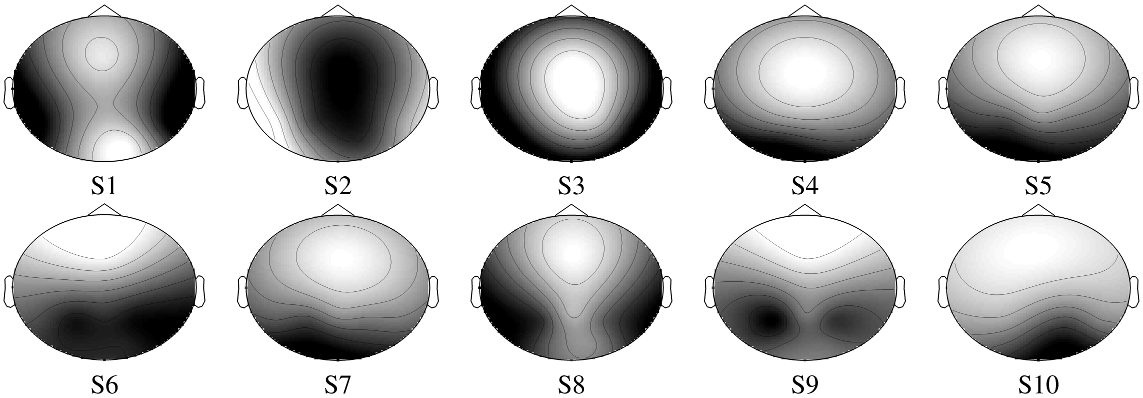

Fig. 5. Spatial distribution with the method GS, ERP after spatial filtering (the best spatial filter). A dark value represents a high SSNR.

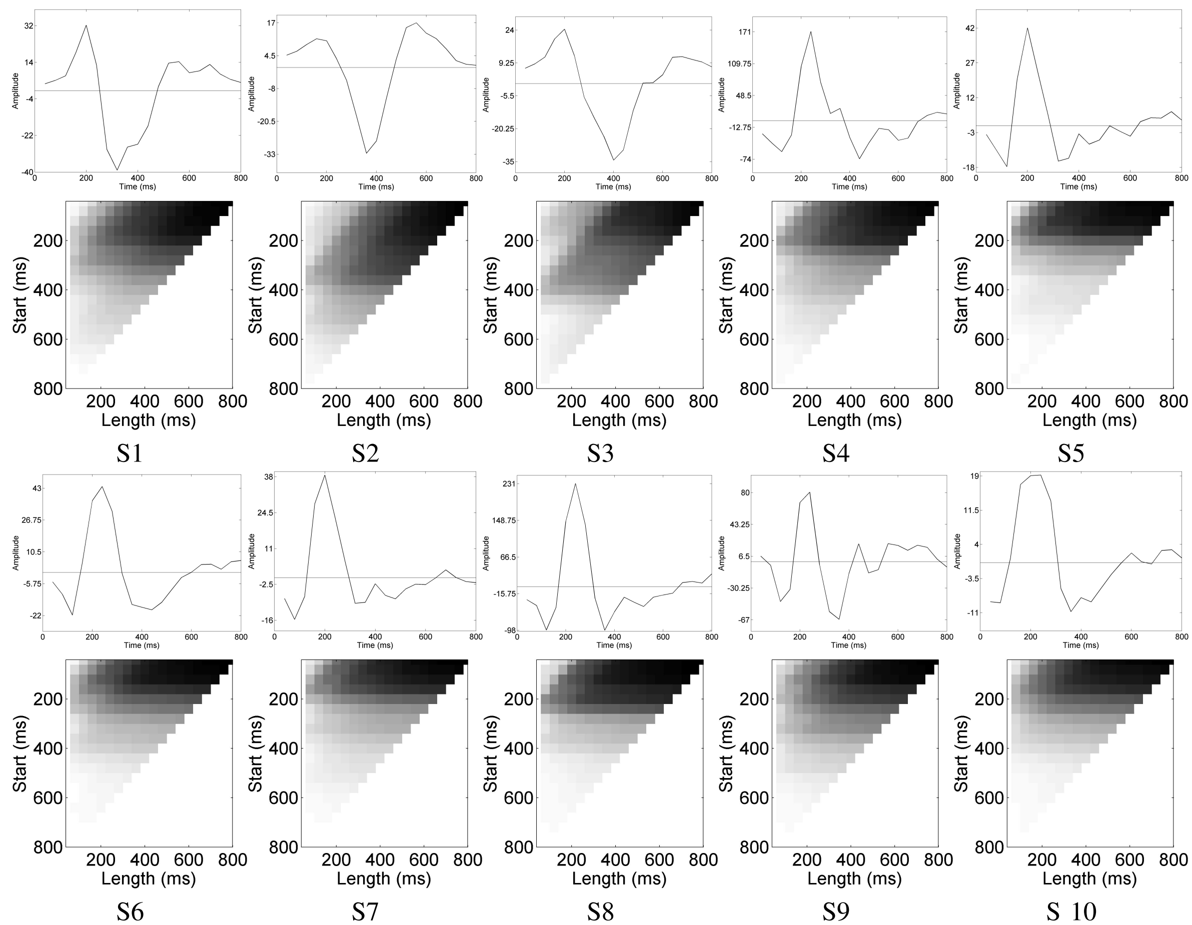

Fig. 6. SSNR (arbitrary unit) as a function of the start of the time-segment and its length. A dark value represents a high SSNR.

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